An Automatic Finite-Sample Robustness Metric: Can Dropping a Little Data Make a Big Difference?

Ryan Giordano (rgiordan@mit.edu)[1]
January 2022

[1]With coauthors Rachael Meager (LSE) and Tamara Broderick (MIT)

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The conclusions of one's statistical analysis may depend on only a **small fraction of the data**, even for **highly significant results in correctly specified models**.

We provide a **generally applicable tool** to detect such sensitivity. Our methods are **efficiently and automatically computable**, and come with **finite-sample accuracy guarantees** and **clear intuition**.

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Dropping data: Mexico Microcredit

Example: Angelucci et al. [2015], a randomized controlled trial study of the efficacy of microcredit in Mexico based on 16,560 data points. The variable "Beta" estimates the effect of microcredit in US dollars.

	Beta (SE)
Original result	-4.55 (5.88)

The original conclusion: No evidence that microcredit is effective...

$\Rightarrow$ Standard errors can be inadequate summaries of data sensitivity!

Cannot find influential subsets by brute force! $\binom{16,560}{15} \approx 1.5 \cdot 10^{51}$

We provide a fast, automatic tool to approximately identify the most influential set of points.

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...can be reversed by dropping less than 0.1% of the data.

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Outline

- Why and when might you care about sensitivity to data dropping?
- How does our approximation work, and when is it accurate?

  (A formalization of the problem and the class of estimators we study.)
- Examine real-life examples of analyses: some sensitive, some not.

  (The results may defy your intuition.)
- What kinds of analyses are sensitive to data dropping?

  (Including comparison to standard errors and gross-error robustness.)

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Would you be concerned if you could **reverse your conclusion** by removing a **small proportion** (say, 0.1%) of your data?

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Would you be concerned if you could **reverse your conclusion** by removing a **small proportion** (say, 0.1%) of your data?

Not always! But sometimes, surely yes.

Thinking without random noise can be helpful.

Suppose you have a farm, and want to know whether your average yield is greater than 170 bushels per acre. At harvest, you measure 200 bushels per acre.

- Scenario one: If your yield is greater than 170 bushels per acre, you make a profit.
  - Don't care about sensitivity to small subsets
- Scenario two: You want to recommend your farming methods to a friend across the valley.
  - Might care about sensitivity to small subsets

For example, often in economics:

- Small fractions of data are missing not-at-random,
- Policy population is different from analyzed population,
- We report a convenient summary (e.g. mean) of a complex effect,
- Models are stylized proxies of reality.

Formalizing the question.

Ordinary least squares

A data point d_n has regressors x_n and response y_n: $d_n = (x_n, y_n)$.

The estimator $\hat{\theta} \in \mathbb{R}^P$ satisfies:

$$\hat{\theta} := \underset{\theta}{\arg\min} \frac{1}{2} \sum_{n=1}^{N} \left(y_n - \theta^T x_n\right)^2$$

$$\Leftrightarrow \sum_{n=1}^{N} \left(y_n - \hat{\theta}^T x_n\right) x_n = 0.$$

Make a qualitative decision using:

- A particular component: θ_k
- The end of a confidence interval: $\theta_k + \frac{1.96}{\sqrt{N}} \hat{\sigma}(\hat{\theta})$

Z-estimators

We observe N data points $d_1, \ldots, d_N$ (in any domain).

The estimator $\hat{\theta} \in \mathbb{R}^P$ satisfies:

$$\sum_{n=1}^{N} G(\hat{\theta}, d_n) = 0_P.$$

$G(\cdot, d_n)$ is "nice," $\mathbb{R}^P$-valued. E.g. OLS, MLE, VB, IV &c.

Make a qualitative decision using $\phi(\hat{\theta})$ for a smooth, real-valued ϕ.

Question: Can we make a big change in $\phi(\hat{\theta})$ by dropping $\lfloor \alpha N \rfloor$ datapoints, for some small proportion α?

Which estimators do we study?

We have N data points $d_1, \ldots, d_N$, a quantity of interest $\phi(\hat{\theta})$, and

$$\sum_{n=1}^{N} G(\hat{\theta}, d_n) = 0_P.$$

Question: Can we make a big change in $\phi(\hat{\theta})$ by dropping $\lfloor \alpha N \rfloor$ datapoints, for some small proportion α? **Two big problems:**

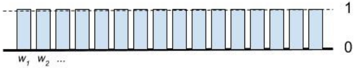
- There are $\binom{N}{\lfloor \alpha N \rfloor}$ sets to check. (Huge even for $\alpha \ll 1$.)
- Evaluating $\hat{\theta}$ re-solving the estimating equation.
  - E.g., re-computing the OLS estimator.
  - Other examples are even harder (VB, machine learning)

An approximation is needed!

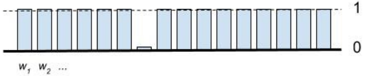
Which estimators do we study?

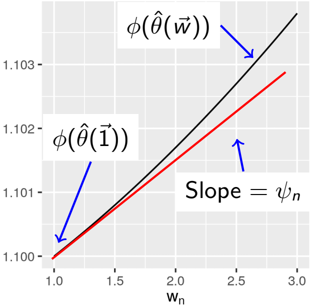
$$\hat{\theta} := \vec{\theta} \text{ such that } \sum_{n=1}^{N} G(\vec{\theta}, d_n) = 0_P.$$

Original weights: $\vec{1} = (1, \ldots, 1)$



Leave points out by setting their elements of $\vec{w}$ to zero.





The slopes $\psi_n := \left.\frac{\partial \phi(\hat{\theta}(\vec{w}))}{\partial \vec{w}_n}\right|_{\vec{1}}$ are values of the **empirical influence function** [Hampel, 1986]. We call them "influence scores."

Second-order derivatives control the error of the linear approximation.

Which estimators do we study?

$$\hat{\theta}({\color{red}\vec{w}}) := \vec{\theta} \text{ such that } \sum_{n=1}^{N} {\color{red}\vec{w}_n} G(\vec{\theta}, d_n) = 0_P.$$

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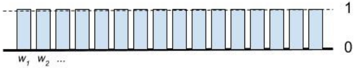

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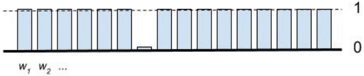

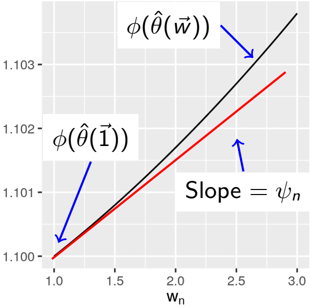

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Taylor series approximation.

Problem: How large can you make $\phi(\hat{\theta}(\vec{w}))$ leaving out no more than $\lfloor \alpha N \rfloor$ points? **Combinatorially hard!**

To simplify the search over $\vec{w}$, we form the Taylor series approximation:

$$\phi(\hat{\theta}(\vec{w})) \approx \color{red}{\phi^{\mathrm{lin}}(\vec{w})} := \phi(\hat{\theta}(\vec{1})) + \sum_{n=1}^{N} \psi_n (\vec{w}_n - 1)$$

Approximate solution: How large can you make $\phi^{\mathrm{lin}}(\vec{w})$ leaving out no more than $\lfloor \alpha N \rfloor$ points? **Easy!**

The most influential points for $\phi^{\mathrm{lin}}(\vec{w})$ have the most negative ψ_n.

The ψ_n are automatically computable using the **implicit function theorem** and **automatic differentiation**.

We provide **finite-sample theory** showing that

$$\left| \phi(\hat{\theta}(\vec{w})) - \phi^{\mathrm{lin}}(\vec{w}) \right| = O\left(\left\| \frac{1}{N}(\vec{w} - \vec{1}) \right\|_2^2 \right) = O(\alpha) \text{ as } \alpha \to 0.$$

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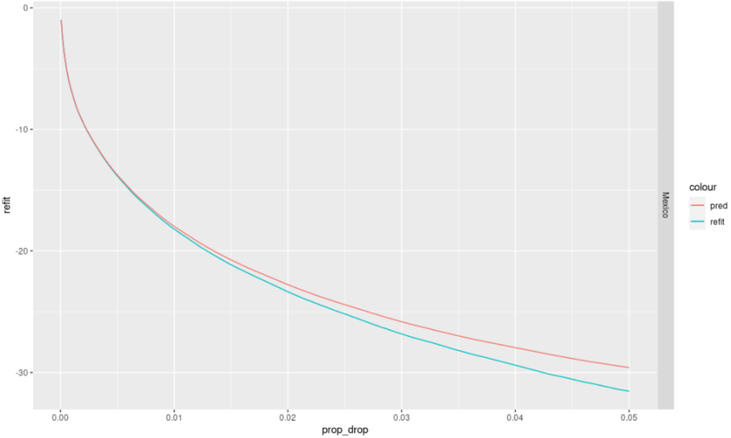
6. **Optional:** Compute $\hat{\theta}(\vec{w}^*)$, and verify that $\phi(\hat{\theta}(\vec{w}^*)) - \phi(\hat{\theta}) \ge \Delta$.

Mexico example:
See `microcredit_profit_sandbox.R`.



Selected experimental results.

Study case	Original estimate (SE)	Target change	Refit estimate	Observations dropped
Mexico	-4.549 (5.879)	Sign change	**0.398 (3.194)**	$1 = 0.01\%$
		Significance change	**-10.962 (5.565)***	$14 = 0.08\%$
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Poor, period 10	33.861 (4.468)*	Sign change	**-2.559 (3.541)**	697 = 6.63%
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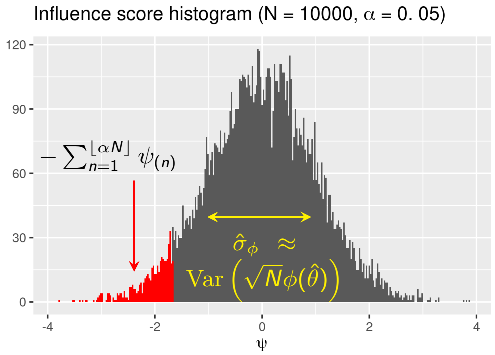
		Significance change	**0.008 (0.005)**	101 = 0.43%
		Significant sign change	**-0.009 (0.004)***	224 = 0.96%

Table: Medicaid profit results [Finkelstein et al., 2012]

What makes an estimator non-robust? A tail sum.

We show that $\phi^{\mathrm{lin}}(\vec{w}^*) - \phi(\hat{\theta}) = -\sum_{n=1}^{\lfloor \alpha N \rfloor} \psi_{(n)} =: \hat{\sigma}_\phi \hat{\mathscr{T}}_\alpha$ where

- The "noise" $\hat{\sigma}_\phi^2 \to \mathrm{Var}(\sqrt{N}\phi)$
  - $\hat{\sigma}_\phi^2 =$ is the robust "sandwich" variance estimator [Hampel, 1986]
- The "shape" $\hat{\mathscr{T}}_\alpha \leq \sqrt{\alpha(1-\alpha)}$ determined by ψ_n distribution
  - $\hat{\mathscr{T}}_\alpha$ converges to a nonzero constant



Example.

Report non-robustness if:

$$\phi^{\text{lin}}(\vec{w}^*) - \phi(\hat{\theta}) = \hat{\sigma}_\phi \hat{\mathscr{T}}_\alpha \ge \Delta \qquad \Leftrightarrow \qquad \frac{\Delta}{\hat{\sigma}_\phi} \le \hat{\mathscr{T}}_\alpha.$$

The **signal to noise ratio** $\frac{\Delta}{\hat{\sigma}_\phi}$ determines sensitivity to data dropping.

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Let's analyze with $\alpha = 0.01 = 1\%$.

$$\begin{aligned} \phi(\hat{\theta}) &= -0.029 && \text{(Increase QOI by defn)} & \Delta &= 0.029 \\ \hat{\sigma}_\phi &= 0.766 && \text{(Noise)} & \tfrac{1}{\sqrt{N}}\hat{\sigma}_\phi &= 0.005 && \text{(SE)} \\ \hat{\mathscr{T}}_\alpha &= 0.046 && \text{(Shape)} & \tfrac{1.96}{\sqrt{N}} &= 0.0128 && \to 0 \text{ as } N \to \infty \\ \hat{\mathscr{T}}_\alpha \hat{\sigma}_\phi &= 0.035 && \text{(Data dropping sensitivity)} & \tfrac{1.96}{\sqrt{N}}\hat{\sigma}_\phi &= 0.010 && \text{(SE sensitivity)} \end{aligned}$$

The noise is much larger than the signal $\Rightarrow$ Sensitive to data dropping.

Corollaries.

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Standard errors reject when $\frac{\Delta}{\hat{\sigma}_\phi} \leq \frac{1.96}{\sqrt{N}} \neq \hat{\mathscr{T}}_\alpha$.

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Corollary: To robustify, reduce the noise or increase the signal.

Other forms of robustness

We proceeded as follows:

1. Took presence of datapoints as a model input,
2. Formed an automatically-computable differential approximation,
3. Provided theory by analyzing higher-order derivatives,
4. Studied its effectiveness in problems with open-access data.

Presence of datapoints is only one model input of many!

- Prior sensitivity in Bayesian nonparametrics [Giordano et al., 2021]
- Model sensitivity of MCMC output [Gustafson, 2000, Giordano et al., 2018]
- Cross-validation [Giordano et al., 2019, Wilson et al., 2020]
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- Frequentist variances of MCMC posteriors (in progress)

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- You may be concerned if you could reverse your conclusion by removing a small proportion of your data.
- We can quickly and automatically find an approximate influential set which is accurate for small sets.
- Robustness to removing small sets is principally determined by the signal to noise ratio.
- In the present work, we studied data dropping. But we provide a framework for studying many other robustness questions, both to data and model perturbations.

Links and references

Tamara Broderick, Ryan Giordano, Rachael Meager (alphabetical authors)
"An Automatic Finite-Sample Robustness Metric: Can Dropping a Little Data Change Conclusions?"
https://arxiv.org/abs/2011.14999

Open-source software:

R package `zaminfluence`	`https://github.com/rgiordan/zaminfluence`
Python package `vittles`	`https://github.com/rgiordan/vittles`

Some related content can be found on my blog:
`https://rgiordan.github.io/`

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